Disaggregated Financial Statement Comparability

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ABSTRACT: This study develops a measure of financial statement comparability based on the disaggregated financial accounting components of earnings. The disaggregated financial statement comparability measure in this paper is contrasted with the aggregated (i.e., based solely on aggregate earnings) financial statement comparability measure used in prior research. The disaggregated framework allows for the measurement of comparability between two firms across multiple components of earnings, and enhances the ability to contrast a company's accounting system to that of other companies impacted by similar economic effects. This comparability measure is robust to a rigorous set of analyses, including tests of incremental informativeness, alternative specifications of comparability, and considerations regarding the information environment. The metric developed in this study extends financial reporting quality and financial statement comparability research based on its ability to capture the distinct components of earnings.

Keywords: Comparability, Earnings Disaggregation, Financial Statement Analysis

Data Availability: Data are available from the public sources cited in the text.

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I. INTRODUCTION

This study develops a new measure of financial statement comparability based on broadly available disaggregated earnings information. Prior research has provided a framework for measuring financial statement comparability in which stock returns (i.e., economic outcomes) are used to determine the extent to which a company's aggregate earnings (i.e., financial statements) are comparable to those of other companies in the same industry (De Franco, Kothari, and Verdi, 2011). This framework has been utilized in recent comparability research (Barth et al. 2012; Chen et al. 2017), however these studies are subject to the same caveat originally identified in De Franco et al. (2011): "only using earnings to capture financial statement comparability is a limitation [of the framework]" (De Franco et al. 2011, 899). In this paper, we construct a new comparability measure based on disaggregated earnings information by leveraging Lipe (1986), who investigates the information content of the components of earnings.

Financial statement comparability is an important characteristic of financial accounting information, according to the FASB, the SEC, investors, and analysts (Financial Accounting Standards Board (FASB) 1978; Securities and Exchange Commission (SEC) 2000; Financial Accounting Standards Board (FASB) 2010; De Franco et al. 2011). Comparable data enables the accounting function to fulfill its purpose of providing useful information to financial statement users in predicting firm performance (i.e., future benefits or cash flows, as well as the riskiness of those cash flows). To be most useful to these interested parties, the accounting information of one company should aid in predicting the future performance of another; this assistance can only be realized if the information is comparable. Two companies are considered financially comparable to the extent that, when facing similar economic outcomes, similar financial statement amounts are reported (i.e., their underlying production functions respond similarly to economic effects) (Financial Accounting Standards Board (FASB) 1980). Given the importance of the quality of comparability within financial reporting, measuring the phenomena in a research setting is of the utmost importance.

In contrast to an aggregated earnings model, a disaggregated earnings model provides a unique coefficient for each disaggregated component of earnings (Lipe 1986). In the returns-earnings model, the regression coefficients can be interpreted as "component shocks" which represent the new information conveyed by each of the components. Persistence in this context is defined as the impact of earnings information on stock returns, and higher (lower) levels of persistence are associated with increased (decreased) levels of stock return response to information in earnings. The stock return reactions to new component information (i.e., the persistence) vary across earnings components because each component induces different levels of revisions in expected future benefits. In other words, varying levels of revision are observed because the information conveyed by each earnings component possesses unique properties. This effect cannot be captured under an aggregated earnings information model. In contrast, a disaggregated system not only more-informatively captures economic effects as they impact a particular company, but also enhances the ability to contrast that company's accounting system to that of other companies, which are impacted by similar economic effects.

Prior financial reporting literature illustrates the informational benefits of disaggregated earnings data. These studies, detailed further in the following section of this paper, suggest that the individual components of earnings provide insights not captured by aggregate earnings due to the incorporation of finer information.[1] Financial statement analysis research provides clear evidence of the forecasting power of decomposed financial data (Kothari 2001; Ou and Penman 1989a, 1989b). Furthermore, from a practice perspective, market participants do not solely consider aggregate earnings in evaluating a company, but rather use multiple facets of the accounting information disclosed by companies. While the use of greater amounts of information in company comparisons is undoubtedly advantageous and consistent with both prior literature and practical application, a measure of comparability constructed from disaggregated data has been absent from the literature to date. The construction of such a measure would effectively link the principles of information disaggregation theory to the study of financial statement comparability, and provide a tool for future research.

In this paper, we first develop the new disaggregated metric. Next, the explanatory power of the accounting system within each comparability framework is examined, wherein the analyses demonstrate the favorable statistical properties of the disaggregated metric over the prior aggregated metric. This is consistent with disaggregated data capturing greater amounts of information that can be used in contrasting companies, and supports the need for a comparability measure based on the same principles. We conduct numerous validation analyses for the disaggregated metric. The validation procedures performed in this paper are consistent with those presented in recent studies that develop new empirical constructs (Sheng and Thevenot 2012; Fengli et al. 2013; Hribar et al. 2014; Chen et al. 2015). Based on these tests, we conclude that the disaggregated metric contributes incremental information beyond that of the aggregated metric.

[1] Prior literature includes: Lipe, 1986; Ou and Penman, 1989a, 1989b; Mcvay, 2006; Ohlson and Penman, 1992; Rayburn, 1986; Weintrop and Swaminathan, 1991; Wilson, 1986; Ball, Gerakos, and Linnainmaa, 2014; Novy-Marx, 2013, Holthausen and Zmijewski, 2014; Kothari, 2001, Fairfield and Yohn, 2001.

Specifically, in our empirics, we first compare the explanatory power of the aggregate and disaggregate approaches. The explanatory power of the disaggregate approach is nearly five times that of the aggregate approach.[2] This is important because this explanatory power is the basis for defining the "accounting system" in the comparability framework. Next, we examine our measure in the multivariate context of analyst forecast accuracy, dispersion, following, and earnings uncertainty. Across these settings, we find the disaggregate comparability measure to be incrementally informative beyond the aggregate measure in explaining these qualities. We then compare our disaggregate comparability metric to a different comparability measure in the literature, one based on accruals. Using the same four contexts, we find the disaggregate measure to be incrementally informative beyond the accruals-based comparability measure. Based upon our empirics, we find the disaggregate-based metric to be a valid proxy for financial statement comparability, and more importantly, the metric out-performs the mostly commonly used metric in the literature.

This study makes several important contributions. First, we develop a more informative, enhanced measure of financial statement comparability – in the sense that the underlying framework incorporates disaggregated accounting information in the prediction of economic outcomes – that is backed by both theoretical and practical support. As disaggregate measures of financial performance capture greater amounts of information about companies, it follows that a measure of comparability constructed from disaggregated data captures higher levels of information available in making comparisons. The disaggregated metric allows for further exploration of the underlying influences of financial statement comparability among firms from

[2] Calculation is 0.4579 / 0.0972 = 4.7109 ~ 5.0. See Table 3.

various perspectives, and has the capability to disentangle the influences of financial statement line items to reveal additional insights that prior aggregate approaches inherently overlook.

Second, this study contributes to the prior disaggregation research as it relates to financial statement comparability. Previous disaggregation studies have found that the information contained within the components of earnings is incremental to that contained in aggregate earnings (Wilson 1987), financial figures other than bottom line earnings contain information about future performance (Ou 1990), and both revenues and expenses provide information beyond their net calculation (Swaminathan and Weintrop, 1991). The current study provides a crucial link between the financial reporting, information disaggregation, and financial comparability literatures.

Finally, this study aligns academic research with professional practice, incorporating the FASB sentiment that focusing on one piece of information in financial reporting is sub-optimal (Financial Accounting Standards Board (FASB) 2010). The disaggregated framework in this study integrates the manner in which financial statement users and market participants actually evaluate companies.

The remainder of this paper is organized as follows. In Section 2, we discuss the relevant background and motivation. We then develop the aggregate and disaggregate financial statement comparability metrics in Section 3. Section 4 outlines the design of the study, followed by the sample selection process and descriptive statistics. Next, Section 5 discusses the main empirical findings and the validation tests. Finally, Section 6 provides concluding remarks.

II. BACKGROUND AND MOTIVATION

Financial Statement Comparability

The purpose of accounting information is to aid financial statement users in predicting future cash flows (i.e., future benefits) and the riskiness of those cash flows. One vital quality of accounting information is that the accounting information of one company be comparable to that of other relevant companies. In the academic literature, the basic idea behind financial statement comparability (FSC) is that accounting amounts are considered comparable if two companies facing similar economic outcomes report similar financial statement amounts. De Franco et al. (2011) explain that comparability is important because financial ratios constructed from accounting information are not necessarily useful by themselves, but rather when contrasted with ratios of comparable firms. The implication is that comparable accounting information is useful because it allows investors to better separate economic effects related to a set of companies in a given industry from all firms in the economy. In other words, the reporting of comparable accounting information of one company can aid in the prediction of future benefits and risks for other companies.

While the financial statement comparability framework of De Franco et al. (2011) employs “reverse regressions” of financial information on economic outcomes, Barth et al. (2012) opt in favor of more “direct regressions" of economic outcomes (i.e., stock returns) on financial information (i.e., earnings) (Barth et al. 2012). Similar to De Franco et al. (2011), the approach in Barth et al. 2012 defines accounting amounts as being comparable if one company’s accounting system (i.e., the mapping between accounting amounts and economic outcomes) produces an estimate of economic outcomes that is similar to that produced by another company’s accounting system. For example, consider two companies: Company I and Company J. To the extent that the financial statements of Company I and Company J are comparable to one another, the use of the accounting information of Company I within the mapping-derived "accounting system" of Company J should approximate the economic outcomes of Company I in a manner similar to the actual economic outcomes for Company I. This approach allows for the measurement of the difference in the estimation of the economic outcomes between the two accounting systems, holding the accounting information constant. A detailed development of this framework is provided in Section 3.

Returns, Earnings, and Information Disaggregation

Underlying the financial statement comparability methodology is the empirical value of the returns-earnings relationship. The study of this relationship originates with Ball and Brown (1968), who argue that due to the importance of earnings data to investors, the usefulness of earnings can be observed by the impact it has in predicting future performance (Ball and Brown, 1968). Subsequent empirical studies provide evidence in support of the informational benefits of disaggregating earnings into its components, which are able to capture more information about companies, as observed via the relationship between stock returns and accounting earnings (Kormendi and Lipe 1987; Lipe 1990; Easton and Harris 1991; Barth et al. 2013).

Prior literature has considered the informational value of financial statement line items and concluded the following: decomposed earnings contain incremental information and usefulness beyond that of the aggregate sum (Ou and Penman 1989a; Ou and Penman 1989b), the information content within individual revenue and expense items is unique and incrementally informative (Weintrop and Swaminathan 1991), and there are distinct and exclusive qualities among the components of earnings generating incremental usefulness (Fairfield, Sweeney, and Yohn 1996). The underlying theme of these studies can be partially traced back to Lev (1989), where it is maintained that capital markets research should focus on the role of accounting measurement rules – such as understanding the use of the financial statement analysis process – and consider the impact of accounting techniques on the predictive power of financial statement items.

Disaggregation in the Comparability Framework

It is important to fully understand the implications of incorporating disaggregated earnings into the financial statement comparability framework. Stock price can be defined as the present value of future benefits and cash flows (and related risks) to financial statement users and market participants. Newly reported accounting information leads to revisions in these estimates of future benefits/cash flows, which influences the stock price and thus the stock return. The extent of the effect of earnings information on stock returns is referred to as ”persistence” in this context, and is explained thoroughly in Lipe (1986) and Kormendi and Lipe (1987). This stream of research considers the persistence of the return-earnings regression coefficients as measures of risk in that the sensitivity of changes in earnings for a given company corresponds to changes in returns of that company. Each component allows for a unique persistence (i.e., a unique impact of each component of earnings on stock returns) to be observed. The regression coefficients can be interpreted as “component shocks” which represent the new information conveyed by each of the components. Stock return reactions to new earnings component information vary across components because each component induces different levels of revisions in future expected benefits; these revisions differ because the information conveyed by each component possesses unique properties (i.e., the autocorrelations and/or cross-correlations of the components are not equal). Specifically, prior research finds that higher (lower) levels of persistence are associated with increased (decreased) levels of stock return response to information in earnings – and the relationship varies across companies depending on the content of the information as it relates to revisions of future expected benefits/cash flows (Kormendi and Lipe 1987).

Empirically, Lipe (1986) shows that new component information is positively related to component persistence, consistent with the view that the additional explanatory power of the components is caused by differences in the properties of the components, which also causes unique investor reaction to each component. Revisions (to expected future earnings) attributable to new information stem from the unique and varying properties of the components of earnings, and in turn, produce unique and varying stock return responses. Applying this theory and research to the current comparability framework enables for the creation of a more informative measure of comparability, as an aggregate earnings comparability approach is unable to allow for the consideration of the unique informational influences of separate earnings components underlying the returns-earnings relationship.

III. METRIC DEVELOPMENT

Aggregated Comparability Measure

The metric development begins with a derivation of the aggregate measure used in Barth et al. (2012). We first regress (by firm-year) quarterly returns onto quarterly earnings – this regression is estimated over sixteen quarters of prior data. Each company is then paired with its industry-year cohort companies, and the following models are presented:

$$RETURNS_{it} = \beta 0_{it} + \beta 1_{it} EARNINGS_{it-1} + \varepsilon_{it} \qquad \textbf{\textit{(1a)}}$$

$$RETURNS_{jt} = \beta 0_{jt} + \beta 1_{jt} EARNINGS_{jt-1} + \varepsilon_{jt} \qquad \textbf{\textit{(1b)}}$$

RETURNS is defined as quarterly buy-and-hold returns.[3] *EARNINGS* is quarterly aggregate earnings (*IBQ*). Specifically, the quarterly returns of one quarter (time t) are regressed on the one-quarter lag (t-1) of earnings (scaled by the market value of equity), given the timing between return realizations and earnings releases. Estimating these regressions produces the "accounting system" for each firm-year observation ($\widehat{\beta 0}_{it}$ / $\widehat{\beta 1}_{it}$ or $\widehat{\beta 0}_{jt}$ / $\widehat{\beta 1}_{jt}$). Because these coefficient estimates are later used to compare other firms' estimations of the current quarter (i.e., fourth quarter) returns, the first estimation (i.e. most recent data for a particular firm-year observation) in the regression model regresses quarter-three *RETURNS* onto quarter-two *EARNINGS*. This ensures that the actual quarter-four returns are not used in calculating the coefficient estimates that are ultimately used to predict quarter-four returns. The main results hold when this is relaxed to begin with fourth quarter returns regressed on third-quarter earnings.

The equations can then be rewritten for each firm first using its own accounting system to estimate its own returns (*iit*), and then using other firms' (based on industry-year) accounting systems to estimate the same returns (*ijt*).

$$E(RETURNS_{iit}) = \widehat{\beta 0}_{it} + \widehat{\beta 1}_{it} EARNINGS_{it-1} \qquad \textbf{\textit{(2a)}}$$

$$E(RETURNS_{ijt}) = \widehat{\beta 0}_{jt} + \widehat{\beta 1}_{jt} EARNINGS_{it-1} \qquad \textbf{\textit{(2b)}}$$

Each company (i.e., Company I) is paired with every other company in the same industry-year (i.e., Company J). The accounting system of Company I ($\widehat{\beta 0_{it}}$ and $\widehat{\beta 1_{it}}$) is applied with its own earnings to estimate its own returns ($RETURNS_{iit}$). Then the accounting system of Company J ($\widehat{\beta 0_{jt}}$ and $\widehat{\beta 1_{jt}}$) is applied with the earnings of Company I to estimate the returns of

[3] Quarterly buy-and-hold returns (*RETURNS*) are calculated as follows: [(Exponential of: the sum of firm-month returns for the three months in each quarter) – 1.00]. Where firm-month returns are calculated as the natural logarithm of: 1.00 + *Monthly Returns* per *CRSP*.

Company I $\left(RETURNS_{ijt}\right)$. The absolute value of the differences between *within* firm (*iit*) and *across* firm (*ijt*) estimates of returns (*B_DIFF*) are averaged over sixteen quarters of data for each firm-pair-year observation.

$$B\_DIFF_{ijt} = E(RETURNS_{iit}) - E\left(RETURNS_{ijt}\right) \tag{3a}$$

$$BCOMP\_PAIR_{ijt} = -\frac{1}{16} \times \sum_{t-15}^{t} \left(\left|B\_DIFF_{ijt}\right|\right) \tag{3b}$$

The average difference is then multiplied by negative one to ease the interpretation (i.e., increasing values represent increased levels of comparability). The resulting variable is referred to as *BCOMP_PAIR*, as it represents the *aggregate*-based financial statement comparability pairing difference.

BCOMP_PAIR represents a firm's differences with each of the other companies (for return estimates) for each year in the sample. Past research (De Franco et al. 2011; Barth et al. 2012; Imhof et al. 2017) has calculated final *firm-year* measures of comparability from each firm-year's pair differences in several ways: the mean of the *four* most comparable firm pairings per firm-year, the mean of the *ten* most comparable firm pairings per firm-year, the mean of *all* firm pairings per firm-year, and the *median* of *all* firm pairings per firm-year. We use the mean of the *seven* most comparable firm pairings per firm-year as this effectively encompasses both the top-four and top-ten approaches. Further, in reality, a particular firm is typically only compared (by investors, analysts, etc.) to a handful of its closest industry cohorts. This final firm-year *aggregate*-earnings-based comparability measure is referred to as *BCOMP* in respect to the original development in Barth et al. (2012).[4]

[4] Results are not materially impacted when using alternative specifications (i.e., mean of the four most or ten most comparable firm pairings per firm year, or the mean/median of all pairings per firm year), consistent with prior studies.

Disaggregated Comparability Measure

Our approach for disaggregated comparability begins by regressing the same quarterly returns on quarterly earnings, consistent with Barth et al. (2012). However, we replace *aggregate* earnings (*EARNINGS*) in the *BCOMP* approach with the *components* of earnings from Lipe (1986) that sum to the *EARNINGS* variable. Lipe (1986) disaggregates earnings into six components – gross profit (*GP*), selling, general and administrative expense (*XSGA*), depreciation expense (*DP*), interest expense (*XINT*), income taxes (*TXT*), and other items (*OTHER*) – (i.e., where *EARNINGS = GP – XSGA – DP – XINT – TXT – OTHER])*.[5] Regarding this choice of components, Lipe (1986) states: "… tests of the information contained in these six components are tests of the information contained in accounting disclosures…there is no one obvious set of components…the six components represent the finest decomposition available from the Compustat items, except that sales and cost of goods sold are combined into gross profit…[because] changes in sales and cost of goods sold are highly correlated…because these two components are driven by similar economic factors." The models are presented below and, similar to the aggregate models, are estimated over sixteen quarters of prior data:

$$\begin{aligned} RETURNS_{it} = {} & L0_{it} + L1_{it}GP1_{it-1} + L2_{it}XSGA1_{it-1} + L3_{it}DP1_{it-1} \\ & + L4_{it}XINT1_{it-1} + L5_{it}TXT1_{it-1} + L6_{it}OTHER1_{it-1} + \varepsilon_{it} \end{aligned} \qquad \textbf{(4a)}$$

$$\begin{aligned} RETURNS_{jt} = {} & L0_{jt} + L1_{jt}GP1_{jt-1} + L2_{jt}XSGA1_{jt-1} + L3_{jt}DP1_{jt-1} \\ & + L4_{jt}XINT1_{jt-1} + L5_{jt}TXT1_{jt-1} + L6_{jt}OTHER1_{jt-1} + \varepsilon_{jt} \end{aligned} \qquad \textbf{(4b)}$$

All components of earnings are lagged one quarter beyond *RETURNS.* Each of the independent variables is scaled by the market value of equity (*MVE*), as is the aggregate earnings variable in the aggregate model. These scaled variables are denoted in the models by the "1"

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[5] *OTHER* can contain various non-recurring items such as minority income, non-operating items, special items, discontinued operations, and extraordinary items (Fairfield et al., 1996).

suffix (e.g., *GP1 = GPQ/MVE*). *GP1* is quarterly gross profit; *XSGA1* is quarterly selling, general, and administrative expenses; *DP1* is quarterly depreciation expense; *XINT1* is quarterly interest expense; *TXT1* is quarterly tax expense; *OTHER1* is equal to the difference between aggregate earnings and the difference between gross profit offset by the five aforementioned quarterly expenses.

Using this data and the above models, the six coefficients (*L0-L6*) are estimated for every firm-year observation. The equations can then be rewritten as *within* firm (*iit*) and *across* firm (*ijt*) estimates of stock returns similar to that done under the aggregate measure discussed earlier:

$$E(RETURNS_{iit}) = \widehat{L0}_{\imath t} + \widehat{L1}_{\imath t}GP1_{it-1} + \widehat{L2}_{\imath t}XSGA1_{it-1} + \widehat{L3}_{\imath t}DP1_{it-1} + \widehat{L4}_{\imath t}XINT1_{it-1} + \widehat{L5}_{\imath t}TXT1_{it-1} + \widehat{L6}_{\imath t}OTHER1_{it-1} \qquad \textbf{\textit{(5a)}}$$

$$E(RETURNS_{ijt}) = \widehat{L0}_{\jmath t} + \widehat{L1}_{\jmath t}GP1_{it-1} + \widehat{L2}_{\jmath t}XSGA1_{it-1} + \widehat{L3}_{\jmath t}DP1_{it-1} + \widehat{L4}_{\jmath t}XINT1_{it-1} + \widehat{L5}_{\jmath t}TXT1_{it-1} + \widehat{L6}_{\jmath t}OTHER1_{it-1} \qquad \textbf{\textit{(5b)}}$$

Under the disaggregated methodology, the accounting system is no longer represented by just the coefficients $\widehat{\beta 0}$ and $\widehat{\beta 1}$ as in the aggregate approach, but rather by the coefficients $\widehat{L0 - L6}$. The average differences between *within* firm (*iit*) and *across* firm (*ijt*) estimates of returns are calculated over the prior sixteen quarters of data for each firm-pair-year observation. Doing this produces the average difference for that particular firm-pair-year, which is then multiplied by negative one for ease of interpretation (i.e., increasing values represent increased levels of comparability). By allowing for several components of earnings in the disaggregated framework, a more representative "accounting system" is constructed that captures the underlying constructs in an enhanced manner based upon information disaggregation theory. In other words, this approach allows for more-informative mapping between accounting data and economic outcomes, as the information content provided by the components of earnings exceed that provided by aggregate earnings alone.

$$L\_DIFF_{ijt} = E(RETURNS_{iit}) - E\big(RETURNS_{ijt}\big) \qquad \textbf{\textit{(6a)}}$$

$$LCOMP\_PAIR_{ijt} = -\frac{1}{16} \times \sum_{t-15}^{t} \left(\left|L\_DIFF_{ijt}\right|\right) \qquad \textbf{\textit{(6b)}}$$

L_DIFF represents the return estimation differences with each of the other companies in the same industry (for return estimates) over each of the sixteen prior quarters (per firm-year). The negative of the absolute value of *L_DIFF* averaged by firm-year is represented by *LCOMP_PAIR*. For the same reasons as under the *BCOMP* methodology, the mean of the *seven* most comparable firm pairings per firm-year is used for the final firm-year FSC measure. This final firm-year disaggregate-earnings-based measure is referred to as *LCOMP* in respect to Lipe (1986).[6] See Appendix B for a detailed example illustrating the calculation of *LCOMP*. Overall, the disaggregated comparability framework represents the relationship between the reporting of events, and the realized consequences of the events. A disaggregated earnings approach to financial statement comparability produces a system that is finer in the sense that it captures and incorporates more information about a company.

IV. RESEARCH DESIGN

Comparability and Analysts

We contrast the aggregated and disaggregated metrics primarily in the context of analyst forecasts, as the setting is valuable for understanding the economic consequences of financial

[6] The results are not materially affected when using alternative specifications (i.e., mean of the four most or ten most comparable firm pairings per firm year, or the mean/median of all pairings per firm year), consistent with prior studies.

disclosures across companies. The qualities of accuracy and dispersion of analyst forecasts represent uncertainty about future performance, and because informational demand is increasing with improvements (i.e., higher accuracy and lower dispersion) in these qualities, more costly information acquisition can result (Barron and Stuerke 1998). Further, the amount of dispersion in analyst forecasts is indicative of uncertainty in the information environment, which includes the comparative quality of financial statements (Barron et al. 2009; Barron and Stuerke 1998; Barron et al. 1998). Increased levels of comparability can lower the cost of obtaining information, which encourages a higher quality and quantity of information, which becomes more widespread. This enables analysts to forecast company performance more consistent with one-another, which leads to forecasts that are more tightly clustered with reduced outliers. For example, the use of uncommon accounting methods – which ultimately produces financial statements that are low in comparability with others – is associated with decreased forecast accuracy and increased forecast dispersion. This indicates that deviating from common, wide-spread accounting procedures leads to increased costs of information analysis as increased effort is needed to adjust for accounting system differences (Bradshaw et al. 2009).

We also consider another analyst trait: analyst following – defined as the number of analysts covering a particular company – is a function of the costs and benefits of coverage to analysts, and stems from information demand, while corresponding to information availability. Increased levels of financial statement comparability are indicative of a better information environment (i.e., higher levels of information availability). Further, because analysts primarily interpret new information, as opposed to convey new information, the more analysts covering a particular company, the more information desired by analysts about that company. Prior research finds that an increase in comparability results in an increase in analyst following (De Franco et al. 2011).

Consistent with the related prior literature, a construct of financial statement comparability should be positively associated with forecast accuracy because increased availability of information about comparable firms lowers the cost of acquiring information, and increases the overall quantity and quality of company information available. Similarly, a construct of financial statement comparability should be negatively associated with forecast dispersion. This enhanced information facilitates analysts' ability to forecast performance by allowing for a more-informative explanation of historical performance or the use of information from comparable firms as additional input in their earnings forecasts, resulting in lower forecast dispersion. Moreover, a proper construct of comparability should be positively associated with analyst following, as analyst tend to follow comparable companies, as documented in prior literature. The following models are utilized in evaluating analyst forecast accuracy and dispersion:

$$ACCURACY_{it} = \delta_0 + \delta_1 XCOMP_{it-1} + \delta_{2-k} CONTROLS_{it-1} + \varepsilon \qquad \textbf{(07)}$$

$$DISPERSION_{it} = \gamma_0 + \gamma_1 XCOMP_{it-1} + \gamma_{2-k} CONTROLS_{it-1} + \varepsilon \qquad \textbf{(08)}$$

$$AFOLL_{it} = \omega_0 + \omega_1 XCOMP_{it-1} + \omega_{2-k} CONTROLS_{it-1} + \varepsilon \qquad \textbf{(09)}$$

In the above equations, *XCOMP* represents either the aggregated comparability measure (*BCOMP)* or the disaggregated comparability measure (*LCOMP)*. *ACCURACY* is the absolute value of the forecast error multiplied by negative 100, scaled by the prior year-end stock price. The forecast error represents the I/B/E/S analysts' mean annual earnings forecast less the actual earnings realized. For a given year, the earliest forecast available is used (e.g., for a calendar year-end company, it is the earliest forecast between January and December of that year). *DISPERSION* is the standard deviation of individual analysts' annual forecasts, scaled by the prior stock price. *AFOLL* is the number of analysts following a company in a given year. Control variables include: *SUE* (the absolute value of unexpected earnings – where the expectation is based on the prior year's actual earnings – scaled by the stock price at the end of the prior year, *NEG_UE* (an indicator equal to one if the earnings are below the reported earnings a year ago, and zero otherwise), *LOSS* (an indicator variable equal to one if current earnings are negative, and zero otherwise), *NEG_SI* (equal to the absolute value of the special item deflated by total assets if negative, and zero otherwise), *DAYS* (a measure of the forecast "horizon," calculated as the natural logarithm of the number of days from the forecast date to the firm's earnings announcement date), *SIZE* (the natural logarithm of total assets), *EPRED* (the R-squared from a firm-specific regression model of earnings on lagged earnings with sixteen quarters of data), *EVOL* (the standard deviation of quarterly earnings (scaled by assets) during the sixteen quarter period used to estimate comparability), and *RVOL* (the standard deviation of monthly returns during the sixteen quarter period used to estimate comparability.

Following De Franco et al. (2011) for the regressions with analyst following as the dependent variable, additional controls are utilized: *BTM* is the ratio of book equity to market equity; *VOLUME* is the logarithm of the trading volume in millions of shares; *RD* is the company's R&D expense (scaled by sales), less the industry average R&D (scaled by sales); *DEPR* is the company's depreciation expense (scaled by sales), less the industry average depreciation expense (scaled by sales); *ISSUE* is an indicator variable equal to 1 if the company issues debt or equity securities in the year, and zero otherwise.

Consistent with prior literature, all control variables represent the one-year lag (i.e., prior year) value, and are winsorized at the 1st and 99th percentiles; industry fixed effects are included, and standard errors are clustered at the firm and year levels (Petersen 2008).

Comparability and Earnings Uncertainty

We also consider Donelson and Resutek (2015), who develop a measure of earnings uncertainty that is neither linked with prior period earnings, nor incorporates analyst forecasts in its derivation, and discuss its use as a measure of the information environment. The authors find that this measure of earnings uncertainty is associated with analyst forecast quality and investor decision making. To calculate this measure, each firm-year observation is matched with other firms in the same industry over the prior five years based on size, earnings, and change in earnings. The standard deviation of realized earnings changes of the matched firms is then calculated. This represents a measure of a firm's earnings uncertainty around its next-year earnings expectations. The logic underlying our usage of this measure is in line with that related to analyst forecast dispersion above.

$$R\_EU_{it} = \mu_0 + \mu_1 XCOMP_{it-1} + \mu_{2-k} CONTROLS_{it-1} + \varepsilon \qquad \textbf{(10)}$$

Where *R_EU* represents the decile rank (by year) of the earnings uncertainty (*EU*) measure. All other variables are as previously defined. A construct of financial statement comparability should be negatively associated with earnings uncertainty. This enhanced information facilitates information transfer by allowing for a more-informative explanation of historical performance or the use of information from comparable firms as additional input, resulting in lower earnings uncertainty.

Incremental Information Content

We conduct numerous validation analyses for the disaggregated comparability metric, and the validation procedures performed in this paper are consistent with those presented in recent studies that develop empirical constructs (Sheng and Thevenot 2012; Fengli et al. 2013; Hribar et al. 2014; Chen et al. 2015). The most direct method to examine incremental information content is a regression model employing a property (i.e., accuracy, dispersion, following, or earnings uncertainty) as the dependent variable and including both *BCOMP* and *LCOMP* as independent variables. However, due to natural multicollinearity issues between *BCOMP* and *LCOMP*, we use a transformation approach in order to contrast *LCOMP* with *BCOMP* in a multivariate model. Specifically, we regress *LCOMP* onto *BCOMP*, and save the residual (*INCREM*) from the regression estimation. The residual represents the information contained within *LCOMP* that is not captured by *BCOMP* (i.e., the incremental information content of the disaggregated model). This residual (*INCREM*) is then included (in addition to *BCOMP*) in each of the four previous regressions with *ACCURACY*, *DISPERSION*, *AFOLL,* and *R_EU* as dependent variables, respectively. The same control variables are included as in previous analyses, and to the extent that *LCOMP* captures and provides additional valuable information, we expect to observe a significant positive relationship for *INCREM* with forecast accuracy and analyst following, and a significant negative relationship for *INCREM* with forecast dispersion and earnings uncertainty.

We also investigate the incremental information content of the disaggregate metric by considering an accrual-based measure of financial comparability (Kawada 2014; Francis et al. 2014). In the accruals-based comparability approach, each company is matched with every other company in the same industry-year, where industry is based on the two-digit SIC code. The pairs can be analyzed in terms of total accruals.[7] Within each pairing, the difference in total accruals between the two companies is calculated, and the median of the absolute value of the differences is derived. This value is then multiplied by negative one so that increasing values represent increased comparability based on total accruals. This measure of financial statement comparability is referred to as *TCOMP*, as it represents a total-accruals approach to comparability. For our analysis, we use *TCOMP* as the baseline measure of financial statement comparability and estimate the models (with dependent variables being *ACCURACY*, *DISPERSION*, *AFOLL*, and *R_EU*, respectively) first using only *TCOMP* as the comparability construct. We then re-estimate the models including *LCOMP* in addition to *TCOMP*. To the extent that our disaggregated comparability measure provides additional and useful information, we expect there to be a positive (negative) and significant relationship between *LCOMP* and analyst accuracy and following (dispersion and earnings uncertainty), even with the inclusion of the *TCOMP* aggregate comparability metric in the model.

Sample Selection

Our sample selection process is detailed in Table 1. The sample begins with the intersection of quarterly data from Compustat and CRSP from 1980 to 2015. This results in 322,296 (1,286,718) firm-year (firm-quarter) observations. Observations with missing earnings components data, observations with negative equity values, and observations missing return data are eliminated. Companies in the utility and financial industries are also removed.[8] At this point, the resulting sample size is 113,031 (428,804) firm-year (firm-quarter) observations.

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[7] Total accruals are defined as *[(ACT-ACT_LAG1) – (LCT-LCT_LAG1) – (CHE-CHE_LAG1) + (DLC – DLC_LAG1)] * (1/AT_LAG1)*. If missing, total accruals are defined as *[IB – (OANCF – XIDOC)] / AT_LAG1*.
[8] Utility (financial) sector companies are defined as those in the SIC range 4900-4999 (6000-6999).

[Insert Table 1 here]

As part of the methodology, each firm-year observation is required to have at least fourteen non-missing quarters of necessary information over the previous sixteen quarters. We remove firm-year observations lacking this data requirement. Doing so reduces the number of firm year observations to 59,216. Appending the previous fourteen to sixteen quarters of data to each remaining firm-year observation brings the number of firm-quarter observations to 877,345. This suggests that on average, each firm-year observation has 14.82 prior quarters of appended data. This dataset is used in the demonstration of the returns-earnings mapping. Finally, each firm is required to have at least ten industry firm pairs in each year based on the two-digit SIC code; those companies without ten or less pairings are removed from the sample. The sample consists of 54,541 firm-year observations. Within this dataset, there are 6,005 unique firms represented across the sample period. In analyses involving analyst forecasts and earnings uncertainty, the sample is restricted to firms meeting all sufficient data requirements, resulting in 15,106 firm-year observations.

Descriptive Statistics

Panel A of Table 2 displays the raw quarterly variables from Compustat. All continuous variables have been winsorized at the 1% and 99% percentiles. The magnitude of the earning components (both in terms of means and medians), from largest to smallest is *GPQ*, *XSGAQ*, *DPQ*, *TXTQ*, *XINTQ*, and *OTHERQ*. Unless otherwise noted, figures are reported in *millions* of dollars. The mean (median) of *MVE* is 1,416.75 (111.41), while the mean (median) of quarterly earnings denoted *IBQ* is 16.49 (0.60). The mean (median) gross profit percent (i.e., *GPQ* / *REVTQ*) is about 33.32% (31.40%). A rough estimate of the mean (median) effective tax rate is

34.67% (32.58%), calculated as *TXTQ* divided by the sum of *IBQ* and *TXTQ*. Overall, these descriptive statistics appear reasonable and consistent with prior studies.

[Insert Table 2 here]

Panel B of Table 2 presents the coefficient estimates for the aggregate and disaggregate models. The intercept from the aggregate model (*B0_I*) has a mean (median) of -0.01 (0.00), while the aggregate earnings coefficient (*B1_I*) has a mean (median) of 2.38 (0.95). The mean (median) values of the coefficients from the disaggregated framework are -0.17 (-0.17), 1.47 (1.07), 0.26 (0.01), 4.15 (1.96), -0.94 (0.00), 0.03 (0.00), -1.60 (-0.66) for the intercept (*L0_I*), gross profit (*L1_I*), SG&A expense (*L2_I*), depreciation expense (*L3_I*), interest expense (*L4_I*), tax expense (*L5_I*), and other (*L6_I*), respectively. In the estimation of returns within the FSC framework, these coefficients are used with the actual values of the related financial statement line items to arrive at a prediction as part of the accounting system.

V. EMPIRICAL FINDINGS

Explanatory Power

The disaggregated framework is first compared to the aggregated framework from prior literature by considering model fit in the returns-earnings regression. To the extent that the disaggregated approach enables for an improved fit in the returns-earnings relationship, a more informative mapping between accounting inputs and economic outcomes is achieved. This can support the benefits of the proposed framework, as it accommodates the unique properties of earnings, including their respective information shocks, persistence levels, and expectation-revision tendencies. Table 3 reports an average R^2 for the aggregated model of 0.0972. The average adjusted R^2 is the same, since the model includes only one explanatory variable. In contrast, for the disaggregated model, the average R^2 (adjusted R^2) is 0.4579 (0.1868). A t-test of the differences of these means reveals that the fit of the disaggregated model is statistically greater than that of the aggregated model, as evidenced by t-statistics of 392.11 for the R^2 difference and 70.83 for the adjusted R^2 difference.

[Insert Table 3 here]

Table 4 contains the descriptive statistics for the aggregate (*BCOMP*) and disaggregate (*LCOMP*) measures. The mean (median) value of *BCOMP* is -2.82 (-2.08), while the mean (median) value of *LCOMP* is -27.29 (-18.23). The standard deviation of *LCOMP* (*BCOMP*) is 28.44 (2.35). The interquartile range begins at -30.10 (-3.58) and ends at -12.09 (-1.23) for *LCOMP* (*BCOMP*). We note that a comparison of *LCOMP* and *BCOMP* descriptive statistics does not, in itself, provide evidence of one being a more appropriate proxy for comparability than the other. The aggregate and disaggregate measures represent an averaged difference in the estimation of returns using own versus cross-company accounting systems. On average, *LCOMP* values are roughly ten times larger in absolute magnitude than *BCOMP* values. The *LCOMP* framework utilizes the various components of earnings to construct the accounting system. Doing so allows for more flexibility and representativeness of the intricacies of unique firms' accounting systems, which allows for enhanced interpretations.

[Insert Table 4 here]

Table 5 presents descriptive statistics for the analyst forecast analyses. The sample is restricted to firms meeting all necessary data requirements. From the main dataset, observations not meeting the data requirements are removed from the sample. This results in a sample size of 15,106 firm-year observations. *ACCURACY* has a mean (median) of -4.17 (-0.96), while

DISPERSION has a mean (median) of 0.02 (0.00) – these figures are in line with prior literature.[9] *AFOLL*, *INCREM*, *TCOMP*, and *EU* have mean (median) values of 12.98 (10.00), 1.03 (5.38), -0.12 (-0.11), and 0.06 (0.03), respectively. The mean values of the indicator variables are as follows: 0.40 (*NEG_UE*) – suggesting that, on average, 40% of firms reported earnings below prior year earnings, 0.24 (*LOSS*) – indicating that 24% of firms experience losses each year, and 0.02 (*NEG_SI)* – indicating that 2% of the observations have negative special items. In addition, the mean value of *DAYS* is 3.67, which is a logged value that converts (e^3.67) to about thirty-nine actual calendar days from the forecast date to the earnings announcement date. Descriptive statistics for *EPRED*, *EVOL*, *RVOL*, *BTM*, *VOLUME*, *RD*, *DEPR*, and *ISSUE* all appear reasonable and in line with expectations.

[Insert Table 5 here]

Incremental – Versus BCOMP

Due to natural multicollinearity issues between the aggregated and disaggregated comparability measures, we use a transformation approach to contrast the disaggregated comparability measure (*LCOMP)* with the aggregated comparability measure (*BCOMP)* in multivariate models. The residual (*INCREM*) from the regression of *LCOMP* onto *BCOMP* is included in regressions using *BCOMP* to proxy for financial statement comparability along with additional control variables detailed previously in the research design section.

The results related to forecast accuracy (dispersion) are presented in Panel A (Panel B) of Table 6. The first regression regresses analyst forecast accuracy on *BCOMP* and the control

[9] In De Franco et al. (2011), *ACCURACY* [*DISPERSION*] has a mean (median) of -5.0 (-1.1) [0.9 (0.3)].

variables. The coefficient on *BCOMP* (0.21) is positive and significant (t-statistics = 4.27). The second regression replaces *BCOMP* with *LCOMP*. The coefficient on *LCOMP* (0.01) is positive and significant (t-statistic = 3.44). The third regression is the same as the first, except it also includes *INCREM*. The coefficient on *BCOMP* remains significant, and the coefficient on *INCREM* (0.01) is positive and significant (t-statistic = 1.86). As *INCREM* is the information in *LCOMP* not captured by *BCOMP*, the results indicate that *LCOMP* provides additional information as related to analyst forecast accuracy. This suggests that the disaggregated framework produces a measure of comparability that is incrementally informative to the aggregated measure in explaining forecast accuracy.

The regression with analyst forecast dispersion as the dependent variable reported in Panel B of Table 6. The first regression regresses analyst forecast dispersion on *BCOMP* and the control variables. The coefficient on *BCOMP* (0.00) is negative and significant (t-statistic = -4.65). The second regression replaces *BCOMP* with *LCOMP*. The coefficient on *LCOMP* (0.00) is negative and significant (t-statistic = -2.49). The third regression is the same as the first, except it also includes *INCREM*. The coefficient on *BCOMP* remains significant, and the coefficient on *INCREM* (0.00) is negative and significant (t-statistic = -1.93). This finding provides further evidence that the disaggregated comparability measure is incrementally informative to the aggregated measure – in this case, in explaining forecast dispersion.

[Insert Table 6 here]

Panel C of Table 6 presents the results of regressions using analyst following as the dependent variable. The first regression regresses analyst following on *BCOMP* and the control variables. The coefficient on *BCOMP* (0.02) is not significant (t-statistics = 0.99). The second regression replaces *BCOMP* with *LCOMP*. The coefficient on *LCOMP* (0.01) is positive and significant (t-statistic = 4.59). The third regression is the same as the first, except it also includes *INCREM*. The coefficient on *INCREM* (0.01) is positive and significant (t-statistic = 3.30), suggesting that the disaggregated framework produces a measure of comparability that is more informative in explaining analyst following.

Panel D of Table 6 presents the results of regressions using earnings uncertainty as the dependent variable, as like analyst forecast dispersion, it too can proxy for uncertainty in the information environment. The first regression regresses earnings uncertainty on *BCOMP* and the control variables. The coefficient on *BCOMP* (-0.07) is negative significant (t-statistics = -6.33). The second regression replaces *BCOMP* with *LCOMP*. The coefficient on *LCOMP* (0.00) is negative and significant (t-statistic = -2.59). The third regression is the same as the first, except it also includes *INCREM*. The coefficient on *INCREM* (-0.05) is negative and significant (t-statistic = -6.66). This further supports the notion that the disaggregated framework produces a measure of comparability that is more informative in explaining uncertainty in the information environment.

Incremental – Versus TCOMP

An alternative measure of comparability between two companies is developed based on total accruals (*TCOMP*). We repeat the previous analyses (accuracy, dispersion, following, and earnings uncertainty) using this alternative comparability measure including the same control variables. The results are reported in Table 7.

In Panel A of Table 7, with accuracy as the dependent variable, the coefficient on *TCOMP* (3.01) is not statistically significant (t-statistic = 1.46). Next, we re-estimate the model including our disaggregated comparability measure (*LCOMP)* in addition to the comparability measure based on total accruals (*TCOMP).* In the regression including both measures, *LCOMP* has a positive coefficient (0.01) that is statistically significant (t-statistic = 3.63). This suggests that *LCOMP* is incrementally informative to a comparability measure based on total accruals in relation to forecast accuracy.

In Panel B of Table 7, with dispersion as the dependent variable, we find a negative coefficient (-0.02) on *TCOMP* that is statistically significant (t-statistic = -2.01), suggesting that increased values of this alternative comparability metric based on total accruals is associated with decreased levels of analyst forecast dispersion. This is in line with expectations based on prior literature (Kawada 2014; Francis et al. 2014). Next, we re-estimate the model including our disaggregated comparability measure (*LCOMP)* in addition to the comparability measure based on total accruals (*TCOMP).* In the regression including both measures, *LCOMP* has a negative coefficient (-0.00) that is statistically significant (t-statistic = -2.75). This suggests that *LCOMP* is incrementally informative to a comparability measure based on total accruals in relation to forecast dispersion.

[Insert Table 7 here]

In Panel C of Table 7, with analyst following as the dependent variable, we find the coefficient on *TCOMP* (-011) to be insignificant (t-statistic = -0.10). Next, we re-estimate the model including our disaggregated comparability measure (*LCOMP)* in addition to the comparability measure based on total accruals (*TCOMP).* In the regression including both measures, *LCOMP* has a positive coefficient (0.01) that is statistically significant (t-statistic = 4.59). This suggests that *LCOMP* is incrementally informative to a comparability measure based on total accruals in relation to analyst following.

In Panel D of Table 7, with earnings uncertainty as the dependent variable, we find a negative coefficient (-2.13) on *TCOMP* that is significant (t-statistic = -4.05). Next, we re-estimate the model including our disaggregated comparability measure (*LCOMP)* in addition to the comparability measure based on total accruals (*TCOMP).* In the regression including both measures, *LCOMP* has a negative coefficient (-0.00) that is statistically significant (t-statistic = -2.97). This suggests that *LCOMP* is incrementally informative to a comparability measure based on total accruals in relation to earnings uncertainty.

VI. CONCLUSION

We advance prior research that uses an aggregated measure of financial statement comparability by developing a disaggregated measure that is aligned with both theoretical and practical support. Underlying the disaggregated financial statement comparability measure is the construction of a finer financial accounting system that enhances the ability to compare one company's reported accounting data to that of other companies in the same industry. Decomposing earnings into a set of informative components allows for the persistence of earnings to vary by component, and more effectively capture the unique changes affecting earnings and present values of revisions in estimates of future benefits (Kormendi and Lipe 1987). In doing so, the accounting system can be more appropriately represented, which allows for the accommodation of unique and varying shocks related to information reporting.

We compare the explanatory power of the aggregate and disaggregate approaches, and find the disaggregate approach to be nearly five times as powerful of the aggregate approach. We then evaluate the disaggregate measure of comparability alongside the aggregate measure in the contexts of analysts and earnings uncertainty, and find the disaggregate comparability measure to be incrementally informative beyond the aggregate measure. Finally, we compare our disaggregate comparability metric to an alternative, accruals-based comparability measure and find similar results. We conclude that disaggregate metric represents a greatly-enhanced proxy for financial statement comparability compared to prior literature to date.

Overall, this study contributes to prior research across several areas (financial reporting, earnings disaggregation, and professional applicability), and provides a crucial link between the financial reporting, information disaggregation, and financial comparability literatures. A new link between academic research and real world application is established as the framework in this paper reflects the manner in which financial analysts and shareholders evaluate companies relative to others.

We anticipate that this measure will be a useful tool for a broad variety of future research and application. For instance, future research could explore the relative benefits of a disaggregated comparability measure by industry. Are there particular industries in which a disaggregated comparability measure provides relatively greater benefits? Another avenue could be to examine the relative contribution of the various earnings components. Do each of the six earnings components contribute similarly in explaining the relation between financial statement comparability and analyst properties such as accuracy and dispersion? Overall, utilizing our disaggregated comparability metric should enable researchers to better capture the underlying construct of financial statement comparability, which will lead to an improvement in the research related thereto.

APPENDIX A: VARIABLE DEFINITIONS

VARIABLE ***DESCRIPTION / CALCULATION***

Returns-Earnings Regression Model

RETURNS	Buy and hold returns	{Exponential of: [Sum of firm-month LOG(Monthly Returns +1) for three months in each quarter]} - 1
MVE	Market value of equity	*PRCC_F * CSHO*
IBQ, or *EARNINGS*	Lagged quarterly earnings, scaled by *MVE*	*IBQ / MVE*
REVTQ	Total revenue	*REVTQ*
COGSQ	Cost of goods sold	*COGSQ*
GPQ	Quarterly gross profit	*REVTQ* - *COGSQ*
GP1	*GPQ*, scaled by *MVE*	*GPQ / MVE*
XSGAQ	Quarterly selling, general, and administrative expenses	*XSGAQ*
XSGA1	*XSGAQ* scaled by *MVE*	*XSGAQ / MVE*
DPQ	Quarterly depreciation expense	*DPQ*
DP1	*DPQ* scaled by *MVE*	*DPQ / MVE*
XINTQ	Quarterly interest expense	*XINTQ*
XINT1	*XINTQ* scaled by *MVE*	*XINTQ / MVE*
TXTQ	Quarterly tax expense	*TXTQ*
TXT1	*TXTQ* scaled by *MVE*	*TXTQ / MVE*
OTHERQ	Quarterly other items	*IBQ – [GPQ - (XSGAQ + DPQ + XINTQ + TXTQ)]*
OTHER1	*OTHERQ* scaled by *MVE*	*OTHERQ / MVE*

Firm Pairing Process

B0_I (B0_J)	Intercept coefficient estimate from the returns-earnings regression	Per the model: *RETURNS = B0_I + B1_I * EARNINGS*
B1_I (B1_J)	*EARNINGS* coefficient estimate from the returns-earnings regression	
L0_I (L0_J)	Firm i's (j's) intercept coefficient estimate from the returns-earnings regression	Per the model: *RETURNS = L0_I + L1_I * GP1 + L2_I * XSGA1 + L3_I * DP1 + L4_I * XINT1 + L5_I * TXT1 + L6_I * OTHER1*
L1_I (L1_J)	Firm i's (j's) *GP1* coefficient estimate from the returns-earnings regression	
L2_I (L2_J)	Firm i's (j's) *XSGA1* coefficient estimate from the returns-earnings regression	
L3_I (L3_J)	Firm i's (j's) *DP1* coefficient estimate from the returns-earnings regression	
L4_I (L4_J)	Firm i's (j's) *XINT1* coefficient estimate from the returns-earnings regression	
L5_I (L5_J)	Firm i's (j's) *TXT1* coefficient estimate from the returns-earnings regression	
L6_I (L6_J)	Firm i's (j's) *OTHER1* coefficient estimate from the returns-earnings regression	

FSC Variables

BCOMP	Average of the seven most comparable *BCOMP_PAIR* values
LCOMP	Average of the seven most comparable *LCOMP_PAIR* values

Additional Variables

INCREM	A measure of the incremental informativeness of LCOMP beyond BCOMP. The residual from regressing LCOMP onto BCOMP.
TCOMP	Alternative FSC metric, based on the difference in total accruals of industry-year paired companies
EU	Earnings uncertainty – per Donelson and Resutek (2015)

Analyst Forecast Analyses

ACCURACY	Absolute value of the forecast error multiplied by −100, scaled by the stock price at the end of the prior fiscal year, where the forecast error is the I/B/E/S analysts' mean annual earnings forecast less the actual earnings as reported by I/B/E/S
DISPERSION	Cross-sectional standard deviation of individual analysts' annual forecasts, scaled by the stock price at the end of the prior fiscal year
AFOLL	Analyst following defined as the number of analysts covering a company in a given year.
SUE	Absolute value of unexpected earnings, scaled by the stock price at the end of the prior year, where unexpected earnings is actual earnings less a forecast based on a seasonal-adjusted random walk time-series model
NEG_UE	Indicator variable that equals one if firm-i's earnings are below the reported earnings a year ago, zero otherwise
LOSS	Indicator equal to one for negative earnings; zero otherwise
NEG_SI	If special items are negative, then equal to the absolute value of special items scaled by total assets, and zero otherwise
DAYS	Logarithm of the number of days from the forecast date to the earnings announcement date
SIZE	Logarithm of the market value of equity
EPRED	R-Squared from the firm-year regression of earnings onto lagged earnings the same firm over 16 prior quarters
EVOL	Standard deviation over prior 16 quarters of earnings
RVOL	Standard deviation over prior 48 months of stock returns
BTM	Book value of equity, scaled by market value of equity
VOLUME	Logarithm of annual trading volume in millions of shares
RD	Firm's R&D (scaled by total sales), less two-digit SIC R&D mean (scaled by total sales)
DEPR	Firm's depreciation expense (scaled by total sales), less two-digit SIC depreciation expense mean (scaled by total sales)
ISSUE	Indicator equal to 1 if the company issued equity or debt securities during the year, and zero otherwise.

APPENDIX B: METHODOLOGY EXAMPLE

Example Connecting Step 5 to Step 7 in Table 1:

- Let *GVKEY_I* = 1773 = "Company I"

- Let YEAR = 2003
    - Year-end = 12/31/2003 (i.e., end of Q4 2003)

- In 2003, Company I has the following 16 observations (i.e., the 16 prior quarters):
    - 2003: Q1, Q2, Q3
    - 2002: Q1, Q2, Q3, Q4
    - 2001: Q1, Q2, Q3, Q4
    - 2000: Q1, Q2, Q3, Q4
    - 1999: Q4

- Quarterly returns are regressed on the one-quarter lagged earnings.

- Each firm is matched to all other companies in the same industry-quarter-year.

- If fewer than ten matched firms, the firm-year observation is dropped from the sample.

- In this example (*SIC2*=50; *YEAR*=2003), there are 77 companies matched.

- Now for example, let one *GVKEY_J* = 8084 = "Company J"
    - There are 16 pairings between Company I and J for this one observation.
    - Returns for Company I are estimated with Company I's earnings via:
        1. The accounting system of Company I
        2. The accounting system of Company J
    - From this, *L_DIFF* can be calculated 16 different times

- Following this, *LCOMP_PAIR* can be calculated, and represents one calculation for one company (Company I) matched with one industry-year cohort company (Company J) for one year (2003) of the sample.

- The firm-year *LCOMP* variable is then calculated as the mean of the seven most comparable observations of *LCOMP_PAIR* (i.e., those closest to zero) from the set of industry-year counterpart-matched observations (77 in this example).

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TABLE 1. SAMPLE SELECTION

METRIC/SAMPLE CONSTRUCTION PROCESS

Step	***Description***	***Firm-Years***	***Firm-Quarters***	***Table***
1	Compustat & CRSP, 1980-2015	322,296	1,286,718	
2	Data Requirement for Earnings Components	-182,337	-758,252	
3	Data Requirement for Buy and Hold Returns	-522	-2,899	
4	Drop Financial and Utility Companies	-26,406	-96,763	
	Preliminary Sample	113,031	**428,804**	**T2PA**
5	Require & Append 14-16 Prior Quarters	-53,815	448,541	
	Returns-Earnings Regression	**59,216**	877,345	**T3**
6	Require 10+ Industry Pairs per Firm-Year	-4,675	-18,700	
7	Firm Pairing Process	54,541	**858,645**	**T2PB**
	Sample with non-missing *BCOMP* & *LCOMP*	**54,541**	*n/a*	**T4PA**
8	Require non-missing regression variables	-39,435		
	Sample for Multivariate Regressions	**15,106**		**T5-T7**

This table illustrates the metric construction process in terms of sample size.

Both firm-year and firm-quarter observations are shown.

Bolded numbers are tied to sample sizes in the tables indicated.

TABLE 2. DESCRIPTIVE STATISTICS

Panel A: Quarterly Data

Variable	N	Mean	Std. Dev.	P25	P50	P75
RETURNS	428,804	0.03	0.30	-0.14	0.00	0.16
MVE	428,804	1416.75	5744.36	26.11	111.41	555.91
IBQ	428,804	16.49	91.37	-0.46	0.60	5.59
REVTQ	428,804	318.17	1186.06	6.52	30.38	143.71
COGSQ	428,804	208.29	787.72	4.10	18.42	90.70
GPQ	428,804	106.00	420.39	1.83	9.54	46.21
XSGAQ	428,804	55.51	206.17	1.33	6.20	26.26
DPQ	428,804	13.75	53.99	0.15	0.92	5.21
XINTQ	428,804	5.51	18.67	0.01	0.27	2.25
TXTQ	428,804	8.75	38.65	0.00	0.29	3.02
OTHERQ	428,804	3.40	54.64	-0.34	-0.01	0.00

RETURNS is the stock return; *MVE* is market value of equity calculated as end of year stock price *(PRCC_F*), multiplied by common shares outstanding *(CSHO); IBQ* is earnings (quarterly)*; REVTQ* is total revenue (quarterly)*; COGSQ* is cost of goods sold (quarterly)*; GPQ* is quarterly gross profit calculated as *REVTQ - COGSQ; XSGAQ* is quarterly sales, general, and administrative expenses*; DPQ* is quarterly depreciation expense*; XINTQ* is quarterly interest expense*; TXTQ* is quarterly tax expense*; OTHERQ* is quarterly other items calculated as *IBQ –[GPQ - XSGAQ - DPQ - XINTQ - TXTQ)]*.

PANEL B: COEFFICIENT ESTIMATES

Variable	N	Mean	Std. Dev.	P25	P50	P75
B0_I	858,645	-0.01	0.12	-0.06	0.00	0.06
B1_I	858,645	2.38	6.96	-0.89	0.95	4.33
L0_I	858,645	-0.17	0.31	-0.36	-0.17	0.02
L1_I	858,645	1.47	29.08	-5.48	1.07	8.91
L2_I	858,645	0.26	41.76	-11.56	0.01	11.77
L3_I	858,645	4.15	57.05	-24.38	1.96	35.45
L4_I	858,645	-0.94	55.68	-27.70	0.00	24.38
L5_I	858,645	0.03	49.33	-17.99	0.00	18.06
L6_I	858,645	-1.60	47.76	-14.49	-0.66	10.71

Coefficient Estimates from the Returns-Earnings Regressions:

Under the Aggregated Framework:

B0**:** intercept

B1**:** *IB1* (*IBQ/MVE*) coefficient

Under the Disaggregated Framework:

L0**:** intercept

L1**:** *GP1* (*GPQ/MVE*) coefficient

L2**:** *XSGA1* (*XSGAQ/MVE*) coefficient

L3**:** *DP1* (*DPQ/ MVE*) coefficient

L4**:** *XINT1* (*XINTQ/MVE*) coefficient

L5**:** *TXT1* (*TXTQ/MVE*) coefficient

L6**:** *OTHER1* (*OTHERQ/MVE*) coefficient

TABLE 3. EXPLANATORY POWER

	N	Mean (Aggregated Model)	Mean (Disaggregated Model)	t-stat	p-value
R-Squared	59,216	0.0972	0.4579	392.11	<0.0001***
Adj. R-Squared	59,216	0.0972	0.1868	70.83	<0.0001***

The above table presents the average explanatory power observed under both the aggregate and disaggregate returns-earnings models underlying the aggregate disaggregate approaches, respectively. The difference in means is statistically examined, and the t-statistics and p-values shown.

TABLE 4. DISAGGREGATED VS. AGGREGATED COMPARABILITY METRIC

Variable	**N**	**Mean**	**Std.**	**P25**	**P50**	**P75**
LCOMP	54,541	-27.29	28.44	-30.10	-18.23	-12.09
BCOMP	54,541	-2.82	2.35	-3.58	-2.08	-1.23

This table presents the descriptive statistics for the new (*LCOMP*) and existing (*BCOMP*) financial statement comparability metrics.

LCOMP Disaggregated-earnings-based comparability metric.

BCOMP Aggregate-earnings-based comparability metric.

TABLE 5. DESCRIPTIVE STATISTICS

Variable	N	Mean	Std.	P25	P50	P75
ACCURACY	15,106	-4.1699	11.2184	-3.0397	-0.9606	-0.2660
DISPERSION	15,106	0.0153	0.0453	0.0013	0.0035	0.0101
AFOLL	15,106	12.9823	10.0275	5.0000	10.0000	18.0000
INCREM	15,106	1.0269	19.2321	-1.6730	5.3760	9.9057
TCOMP	15,106	-0.1153	0.0458	-0.1338	-0.1069	-0.0854
EU	15,106	0.0596	0.0959	0.0164	0.0279	0.0564
SUE	15,106	6.0416	20.3467	0.3020	1.0009	3.7069
NEG_UE	15,106	0.4036	0.4906	0.0000	0.0000	1.0000
LOSS	15,106	0.2386	0.4263	0.0000	0.0000	0.0000
NEG_SI	15,106	0.0187	0.0561	0.0000	0.0011	0.0130
DAYS	15,106	3.6676	0.3699	3.3673	3.6636	3.9512
SIZE	15,106	6.9018	1.8165	5.6406	6.7984	8.0460
EPRED	15,106	0.3715	0.3193	0.0724	0.2982	0.6272
EVOL	15,106	0.3497	0.8879	0.0271	0.0749	0.2397
RVOL	15,106	0.1615	0.0859	0.1049	0.1388	0.1926
BTM	15,106	0.4880	0.4395	0.2531	0.4147	0.6431
VOLUME	15,106	13.5423	1.6854	12.4606	13.5860	14.6717
RD	15,106	-1.1455	11.2993	-0.1805	-0.0003	0.0000
DEPR	15,106	-1.1674	11.1723	-0.2984	-0.0462	0.0140
ISSUE	15,106	0.9565	0.2039	1.0000	1.0000	1.0000

Variables - which can also be found in Appendix A - are defined as follows: *ACCURACY: Absolute value of the forecast error multiplied by (-100), scaled by the stock price at the end of the prior fiscal year, where the forecast error is the I/B/E/S analysts' mean annual earnings forecast less the actual earnings as reported by I/B/E/S. DISPERSION: Cross-sectional standard deviation of individual analysts' annual forecasts, scaled by the stock price at the end of the prior fiscal year. AFOLL: The number of analysts following/covering a company. INCREM: Residual from regressing BCOMP onto LCOMP. TCOMP: An accrual based measure of comparability, as defined in the text. EU: Earnings uncertainty, as defined in the text. SUE: Absolute value of unexpected earnings, scaled by the stock price at the end of the prior year, where unexpected earnings is actual earnings less a forecast based on a seasonal-adjusted random walk time-series model. NEG_UE: Indicator variable that equals one if firm-I has earnings are below the reported earnings a year ago, zero otherwise. LOSS: Indicator variable that equals one if the current earnings are less than zero, zero otherwise. NEG_SI: Absolute value of the special item deflated by total assets if negative, zero otherwise. DAYS: Logarithm of the number of days from the forecast date to the earnings announcement date. SIZE: Logarithm of the market value of equity measured at the end of the year. EPRED: R-squared of a regression of annual earnings on prior-year annual earnings for the same firm. EVOL: Standard deviation of 16 quarterly earnings. RVOL: Standard deviation of 48 months of stock returns. BTM: the ratio of book equity to market equity. VOLUME: the logarithm of the trading volume in millions of shares. RD: the company's R&D expense (scaled by sales), less the industry average R&D (scaled by sales). DEPR: the company's depreciation expense (scaled by sales), less the industry average depreciation expense (scaled by sales). ISSUE: an indicator variable equal to 1 if the company issues debt or equity securities in the year, and zero otherwise.*

TABLE 6. LCOMP VS BCOMP

Panel A: Dependent Variable = Forecast Accuracy

Variable	Coeff.	t-stat	p-value	Coeff.	t-stat	p-value	Coeff.	t-stat	p-value
INTERCEPT	-2.07	-1.66	0.0978 *	-2.16	-1.71	0.0874 *	-2.02	-1.62	0.1063
BCOMP	0.21	4.27	<.0001 ***				0.21	4.33	<.0001 ***
LCOMP				0.01	3.44	0.0006 ***			
INCREM							0.01	1.86	0.0626 *
SUE	-0.09	-6.66	<.0001 ***	-0.09	-6.68	<.0001 ***	-0.09	-6.56	<.0001 ***
NEG_UE	0.06	0.32	0.7503	0.07	0.37	0.7133	0.05	0.28	0.7783
LOSS	-4.64	-13.48	<.0001 ***	-4.68	-13.58	<.0001 ***	-4.64	-13.47	<.0001 ***
NEG_SI	-7.91	-1.68	0.0921 *	-7.53	-1.60	0.1090	-7.89	-1.68	0.0931 *
DAYS	-2.09	-7.54	<.0001 ***	-2.18	-7.96	<.0001 ***	-2.10	-7.57	<.0001 ***
SIZE	1.22	17.71	<.0001 ***	1.24	17.76	<.0001 ***	1.21	17.65	<.0001 ***
EPRED	1.90	8.10	<.0001 ***	1.93	8.22	<.0001 ***	1.89	8.07	<.0001 ***
EVOL	-0.73	-6.46	<.0001 ***	-0.71	-6.25	<.0001 ***	-0.72	-6.39	<.0001 ***
RVOL	-6.40	-4.33	<.0001 ***	-6.97	-4.76	<.0001 ***	-6.37	-4.30	<.0001 ***
	N	**RSQ**	**ADJRSQ**	**N**	**RSQ**	**ADJRSQ**	**N**	**RSQ**	**ADJRSQ**
	15,106	0.1553	0.1548	15,106	0.1544	0.1538	15,106	0.1555	0.1549

Industry fixed effects are included, and standard errors are clustered by firm and year.

Variables - which can also be found in Appendix A - are defined as follows:
ACCURACY: Absolute value of the forecast error multiplied by (−100), scaled by the stock price at the end of the prior fiscal year, where the forecast error is the I/B/E/S analysts' mean annual earnings forecast less the actual earnings as reported by I/B/E/S. *LCOMP:* the disaggregate earnings based measure of comparability. *BCOMP:* the aggregate earnings based measure of comparability. *INCREM:* Residual from regressing *LCOMP* onto *BCOMP*. *SUE:* Absolute value of unexpected earnings, scaled by the stock price at the end of the prior year, where unexpected earnings is actual earnings less a forecast based on a seasonal-adjusted random walk time-series model. *NEG_UE*: Indicator variable that equals one if firm-I has earnings are below the reported earnings a year ago, zero otherwise. *LOSS:* Indicator variable that equals one if the current earnings are less than zero, zero otherwise. *NEG_SI:* Absolute value of the special item deflated by total assets if negative, zero otherwise. *DAYS:* Logarithm of the number of days from the forecast date to the earnings announcement date. *SIZE: L*ogarithm of the market value of equity measured at the end of the year. *EPRED: R*-squared of a regression of annual earnings on prior-year annual earnings for the same firm. *EVOL:* Standard deviation of 16 quarterly earnings. *RVOL:* Standard deviation of 48 months of stock returns.

Panel B: Dependent Variable = Forecast Dispersion

Variable	Coeff.	t-stat	p-value		Coeff.	t-stat	p-value		Coeff.	t-stat	p-value	
INTERCEPT	-0.01	-2.07	0.0386	**	-0.01	-1.87	0.0620	*	-0.01	-2.11	0.0348	**
BCOMP	-0.00	-4.65	<.0001	***					-0.00	-4.71	<.0001	***
LCOMP					-0.00	-2.49	0.0128	**				
INCREM									-0.00	-1.93	0.0536	*
SUE	0.00	7.66	<.0001	***	0.00	7.75	<.0001	***	0.00	7.57	<.0001	***
NEG_UE	0.00	-1.57	0.1158		0.00	-1.65	0.0994	*	0.00	-1.54	0.1245	
LOSS	0.03	17.48	<.0001	***	0.03	17.55	<.0001	***	0.02	17.47	<.0001	***
NEG_SI	0.01	0.48	0.6303		0.01	0.39	0.6978		0.01	0.48	0.6334	
DAYS	0.01	9.19	<.0001	***	0.01	9.67	<.0001	***	0.01	9.23	<.0001	***
SIZE	0.00	-13.84	<.0001	***	0.00	-14.20	<.0001	***	0.00	-13.80	<.0001	***
EPRED	0.00	-5.28	<.0001	***	0.00	-5.40	<.0001	***	0.00	-5.25	<.0001	***
EVOL	0.00	5.38	<.0001	***	0.00	5.20	<.0001	***	0.00	5.31	<.0001	***
RVOL	0.03	5.71	<.0001	***	0.04	6.17	<.0001	***	0.03	5.68	<.0001	***
	N	**RSQ**	**ADJRSQ**		**N**	**RSQ**	**ADJRSQ**		**N**	**RSQ**	**ADJRSQ**	
	15,106	0.1741	0.1735		15,106	0.1724	0.1718		15,106	0.1742	0.1736	

Industry fixed effects are included, and standard errors are clustered by firm and year.

Variables - which can also be found in Appendix A - are defined as follows:
DISPERSION: Cross-sectional standard deviation of individual analysts' annual forecasts, scaled by the stock price at the end of the prior fiscal year. *LCOMP:* the disaggregate earnings based measure of comparability. *BCOMP:* the aggregate earnings based measure of comparability. *INCREM:* Residual from regressing *LCOMP* onto *BCOMP*. *SUE:* Absolute value of unexpected earnings, scaled by the stock price at the end of the prior year, where unexpected earnings is actual earnings less a forecast based on a seasonal-adjusted random walk time-series model. *NEG_UE*: Indicator variable that equals one if firm-I has earnings are below the reported earnings a year ago, zero otherwise. *LOSS:* Indicator variable that equals one if the current earnings are less than zero, zero otherwise. *NEG_SI:* Absolute value of the special item deflated by total assets if negative, zero otherwise. *DAYS:* Logarithm of the number of days from the forecast date to the earnings announcement date. *SIZE: L*ogarithm of the market value of equity measured at the end of the year. *EPRED: R*-squared of a regression of annual earnings on prior-year annual earnings for the same firm. *EVOL:* Standard deviation of 16 quarterly earnings. *RVOL:* Standard deviation of 48 months of stock returns.

Panel C: Dependent Variable = Analyst Following

Variable	Coeff.	t-stat	p-value		Coeff.	t-stat	p-value		Coeff.	t-stat	p-value	
INTERCEPT	-24.21	-39.08	<.0001	***	-24.07	-39.03	<.0001	***	-24.30	-39.23	<.0001	***
BCOMP	0.02	0.99	0.3234						0.03	1.15	0.2513	
LCOMP					0.01	4.59	<.0001	***				
INCREM									0.01	3.30	0.0010	***
SIZE	3.51	51.44	<.0001	***	3.49	51.76	<.0001	***	3.49	51.01	<.0001	***
BTM	2.42	13.33	<.0001	***	2.44	13.45	<.0001	***	2.41	13.28	<.0001	***
VOLUME	0.86	14.95	<.0001	***	0.87	15.22	<.0001	***	0.87	15.13	<.0001	***
RD	-0.03	-1.27	0.2028		-0.03	-0.98	0.3281		-0.03	-1.32	0.1876	
DEPR	0.08	2.92	0.0035	***	0.08	2.93	0.0034	***	0.08	3.10	0.0019	***
ISSUE	-0.65	-2.05	0.0406	**	-0.65	-2.06	0.0397	**	-0.64	-2.03	0.0426	**
EPRED	0.53	2.82	0.0048	***	0.55	2.90	0.0037	***	0.53	2.79	0.0053	***
EVOL	0.70	7.49	<.0001	***	0.72	7.75	<.0001	***	0.72	7.67	<.0001	***
RVOL	4.47	6.34	<.0001	***	4.34	6.16	<.0001	***	4.46	6.33	<.0001	***
	N	**RSQ**	**ADJRSQ**		**N**	**RSQ**	**ADJRSQ**		**N**	**RSQ**	**ADJRSQ**	
	15,106	0.5482	0.5479		15,106	0.5488	0.5485		15,106	0.5485	0.5482	

Industry fixed effects are included, and standard errors are clustered by firm and year.

Variables - which can also be found in Appendix A - are defined as follows:
AFOLL: The number of analysts following/covering a company. *LCOMP:* the disaggregate earnings based measure of comparability. *BCOMP:* the aggregate earnings based measure of comparability. *INCREM:* Residual from regressing *LCOMP* onto *BCOMP*. *SIZE*: Logarithm of the market value of equity measured at the end of the year. *BTM*: the ratio of book equity to market equity. *VOLUME*: the logarithm of the trading volume in millions of shares. *RD*: the company's R&D expense (scaled by sales), less the industry average R&D (scaled by sales). *DEPR*: the company's depreciation expense (scaled by sales), less the industry average depreciation expense (scaled by sales). *ISSUE*: an indicator variable equal to 1 if the company issues debt or equity securities in the year, and zero otherwise. *EPRED: R*-squared of a regression of annual earnings on prior-year annual earnings for the same firm. *EVOL:* Standard deviation of 16 quarterly earnings. *RVOL:* Standard deviation of 48 months of stock returns.

Panel D: Dependent Variable = Earnings Uncertainty (EU)

Variable	Coeff.	t-stat	p-value		Coeff.	t-stat	p-value		Coeff.	t-stat	p-value	
INTERCEPT	4.33	13.26	<.0001	***	4.40	13.46	<.0001	***	4.64	14.10	<.0001	***
BCOMP	-0.07	-6.33	<.0001	***					-0.02	-1.62	0.1061	
LCOMP					-0.00	-2.59	0.0096	***				
INCREM									-0.05	-6.66	<.0001	***
SUE	0.00	2.33	0.0197	**	0.01	2.66	0.0079	***	0.00	2.34	0.0191	**
NEG_UE	-0.25	-5.03	<.0001	***	-0.25	-5.13	<.0001	***	-0.22	-4.52	<.0001	***
LOSS	0.79	10.82	<.0001	***	0.80	10.97	<.0001	***	0.71	9.56	<.0001	***
NEG_SI	6.29	8.94	<.0001	***	6.16	8.73	<.0001	***	6.23	8.89	<.0001	***
DAYS	0.00	-0.05	0.9582		0.03	0.43	0.6662		-0.02	-0.29	0.7731	
SIZE	-0.07	-3.73	0.0002	***	-0.08	-4.34	<.0001	***	-0.07	-3.60	0.0003	***
EPRED	-0.21	-2.80	0.0052	***	-0.22	-2.91	0.0037	***	-0.17	-2.30	0.0217	**
EVOL	0.02	0.56	0.5740		0.01	0.39	0.6939		0.03	1.07	0.2864	
RVOL	1.86	5.95	<.0001	***	2.04	6.54	<.0001	***	1.33	4.15	<.0001	***
	N	**RSQ**	**ADJRSQ**		**N**	**RSQ**	**ADJRSQ**		**N**	**RSQ**	**ADJRSQ**	
	15,106	0.0530	0.0523		15,106	0.0505	0.0499		15,106	0.0561	0.0554	

Industry fixed effects are included, and standard errors are clustered by firm and year.

Variables - which can also be found in Appendix A - are defined as follows:
EU: Earnings uncertainty, calculated per Donelson and Resutek (2015), as described in the text. *LCOMP:* the disaggregate earnings based measure of comparability. *BCOMP:* the aggregate earnings based measure of comparability. *INCREM:* Residual from regressing *LCOMP* onto *BCOMP*. *SUE:* Absolute value of unexpected earnings, scaled by the stock price at the end of the prior year, where unexpected earnings is actual earnings less a forecast based on a seasonal-adjusted random walk time-series model. *NEG_UE*: Indicator variable that equals one if firm-I has earnings are below the reported earnings a year ago, zero otherwise. *LOSS:* Indicator variable that equals one if the current earnings are less than zero, zero otherwise. *NEG_SI:* Absolute value of the special item deflated by total assets if negative, zero otherwise. *DAYS:* Logarithm of the number of days from the forecast date to the earnings announcement date. *SIZE: L*ogarithm of the market value of equity measured at the end of the year. *EPRED: R*-squared of a regression of annual earnings on prior-year annual earnings for the same firm. *EVOL:* Standard deviation of 16 quarterly earnings. *RVOL:* Standard deviation of 48 months of stock returns.

TABLE 7. ALTERNATIVE FSC MEASURE

Panel A: Dependent Variable = Forecast Accuracy

Variable	Coeff.	t-stat	p-value		Coeff.	t-stat	p-value	
INTERCEPT	-2.25	-1.75	0.0794	*	-1.86	-1.45	0.1467	
TCOMP	3.01	1.46	0.1451		3.62	1.76	0.0790	*
LCOMP					0.01	3.63	0.0003	***
SUE	-0.09	-6.88	<.0001	***	-0.09	-6.72	<.0001	***
NEG_UE	0.06	0.32	0.7489		0.05	0.24	0.8106	
LOSS	-4.64	-13.39	<.0001	***	-4.65	-13.42	<.0001	***
NEG_SI	-7.34	-1.56	0.1177		-7.35	-1.57	0.1175	
DAYS	-2.18	-7.98	<.0001	***	-2.16	-7.89	<.0001	***
SIZE	1.26	17.90	<.0001	***	1.24	17.74	<.0001	***
EPRED	1.90	8.13	<.0001	***	1.91	8.15	<.0001	***
EVOL	-0.71	-6.29	<.0001	***	-0.70	-6.16	<.0001	***
RVOL	-6.60	-4.43	<.0001	***	-6.63	-4.46	<.0001	***
	N	**RSQ**	**ADJRSQ**		**N**	**RSQ**	**ADJRSQ**	
	15,106	0.1538	0.1533		15,106	0.1546	0.1540	

Industry fixed effects are included, and standard errors are clustered by firm and year.

Variables - which can also be found in Appendix A - are defined as follows:
ACCURACY: Absolute value of the forecast error multiplied by (−100), scaled by the stock price at the end of the prior fiscal year, where the forecast error is the I/B/E/S analysts' mean annual earnings forecast less the actual earnings as reported by I/B/E/S. *LCOMP:* the disaggregate earnings based measure of comparability. TCOMP: An accrual based measure of comparability, as defined in the text. *SUE:* Absolute value of unexpected earnings, scaled by the stock price at the end of the prior year, where unexpected earnings is actual earnings less a forecast based on a seasonal-adjusted random walk time-series model. *NEG_UE*: Indicator variable that equals one if firm-I has earnings are below the reported earnings a year ago, zero otherwise. *LOSS:* Indicator variable that equals one if the current earnings are less than zero, zero otherwise. *NEG_SI:* Absolute value of the special item deflated by total assets if negative, zero otherwise. *DAYS:* Logarithm of the number of days from the forecast date to the earnings announcement date. *SIZE:* *L*ogarithm of the market value of equity measured at the end of the year. *EPRED: R*-squared of a regression of annual earnings on prior-year annual earnings for the same firm. *EVOL:* Standard deviation of 16 quarterly earnings. *RVOL:* Standard deviation of 48 months of stock returns.

Panel B: Dependent Variable = Forecast Dispersion

Variable	Coeff.	t-stat	p-value		Coeff.	t-stat	p-value	
INTERCEPT	-0.01	-1.91	0.0566	*	-0.01	-2.16	0.0312	**
TCOMP	-0.02	-2.01	0.0440	**	-0.02	-2.23	0.0255	**
LCOMP					-0.00	-2.75	0.0060	***
SUE	0.00	7.92	<.0001	***	0.00	7.81	<.0001	***
NEG_UE	0.00	-1.54	0.1232		0.00	-1.48	0.1388	
LOSS	0.02	17.37	<.0001	***	0.02	17.40	<.0001	***
NEG_SI	0.01	0.34	0.7362		0.01	0.34	0.7357	
DAYS	0.01	9.68	<.0001	***	0.01	9.59	<.0001	***
SIZE	0.00	-14.33	<.0001	***	0.00	-14.18	<.0001	***
EPRED	0.00	-5.27	<.0001	***	0.00	-5.29	<.0001	***
EVOL	0.00	5.20	<.0001	***	0.00	5.10	<.0001	***
RVOL	0.04	5.77	<.0001	***	0.04	5.79	<.0001	***
	N	**RSQ**	**ADJRSQ**		**N**	**RSQ**	**ADJRSQ**	
	15,106	0.1723	0.1718		15,106	0.1728	0.1722	

Industry fixed effects are included, and standard errors are clustered by firm and year.

Variables - which can also be found in Appendix A - are defined as follows:
DISPERSION: Cross-sectional standard deviation of individual analysts' annual forecasts, scaled by the stock price at the end of the prior fiscal year. *LCOMP:* the disaggregate earnings based measure of comparability. *TCOMP*: An accrual based measure of comparability, as defined in the text. *SUE:* Absolute value of unexpected earnings, scaled by the stock price at the end of the prior year, where unexpected earnings is actual earnings less a forecast based on a seasonal-adjusted random walk time-series model. *NEG_UE*: Indicator variable that equals one if firm-I has earnings are below the reported earnings a year ago, zero otherwise. *LOSS:* Indicator variable that equals one if the current earnings are less than zero, zero otherwise. *NEG_SI:* Absolute value of the special item deflated by total assets if negative, zero otherwise. *DAYS:* Logarithm of the number of days from the forecast date to the earnings announcement date. *SIZE: L*ogarithm of the market value of equity measured at the end of the year. *EPRED: R*-squared of a regression of annual earnings on prior-year annual earnings for the same firm. *EVOL:* Standard deviation of 16 quarterly earnings. *RVOL:* Standard deviation of 48 months of stock returns.

Panel C: Dependent Variable = Analyst Following

Variable	Coeff.	t-stat	p-value		Coeff.	t-stat	p-value	
INTERCEPT	-24.29	-38.82	<.0001	***	-24.03	-38.39	<.0001	***
TCOMP	-0.11	-0.10	0.9235		0.38	0.33	0.7421	
LCOMP					0.01	4.59	<.0001	***
SIZE	3.52	51.86	<.0001	***	3.49	51.15	<.0001	***
BTM	2.43	13.13	<.0001	***	2.43	13.09	<.0001	***
VOLUME	0.85	14.86	<.0001	***	0.87	15.15	<.0001	***
RD	-0.04	-1.41	0.1593		-0.03	-1.00	0.3162	
DEPR	0.08	3.04	0.0024	***	0.08	2.94	0.0033	***
ISSUE	-0.65	-2.03	0.0419	**	-0.65	-2.05	0.0405	**
EPRED	0.53	2.82	0.0048	***	0.55	2.88	0.0039	***
EVOL	0.70	7.46	<.0001	***	0.73	7.76	<.0001	***
RVOL	4.44	6.30	<.0001	***	4.36	6.19	<.0001	***
	N	**RSQ**	**ADJRSQ**		**N**	**RSQ**	**ADJRSQ**	
	15,106	0.5482	0.5479		15,106	0.5488	0.5485	

Industry fixed effects are included, and standard errors are clustered by firm and year.

Variables - which can also be found in Appendix A - are defined as follows:
AFOLL: The number of analysts following/covering a company. *LCOMP:* the disaggregate earnings based measure of comparability. *BCOMP:* the aggregate earnings based measure of comparability. *INCREM:* Residual from regressing *LCOMP* onto *BCOMP*. *SIZE*: Logarithm of the market value of equity measured at the end of the year. *BTM*: the ratio of book equity to market equity. *VOLUME*: the logarithm of the trading volume in millions of shares. *RD*: the company's R&D expense (scaled by sales), less the industry average R&D (scaled by sales). *DEPR*: the company's depreciation expense (scaled by sales), less the industry average depreciation expense (scaled by sales). *ISSUE*: an indicator variable equal to 1 if the company issues debt or equity securities in the year, and zero otherwise. *EPRED: R*-squared of a regression of annual earnings on prior-year annual earnings for the same firm. *EVOL:* Standard deviation of 16 quarterly earnings. *RVOL:* Standard deviation of 48 months of stock returns.

Panel D: Dependent Variable = Earnings Uncertainty

Variable	Coeff.	t-stat	p-value		Coeff.	t-stat	p-value	
INTERCEPT	4.30	13.11	<.0001	***	4.21	12.79	<.0001	***
TCOMP	-2.13	-4.05	<.0001	***	-2.26	-4.30	<.0001	***
LCOMP					-0.00	-2.97	0.0030	***
SUE	0.01	3.11	0.0019	***	0.01	2.81	0.0049	***
NEG_UE	-0.24	-4.88	<.0001	***	-0.24	-4.81	<.0001	***
LOSS	0.78	10.61	<.0001	***	0.78	10.66	<.0001	***
NEG_SI	6.04	8.55	<.0001	***	6.04	8.57	<.0001	***
DAYS	0.02	0.29	0.7730		0.01	0.21	0.8350	
SIZE	-0.08	-4.55	<.0001	***	-0.08	-4.32	<.0001	***
EPRED	-0.20	-2.72	0.0065	***	-0.20	-2.73	0.0063	***
EVOL	0.01	0.33	0.7413		0.01	0.22	0.8297	
RVOL	1.82	5.79	<.0001	***	1.83	5.82	<.0001	***
	N	**RSQ**	**ADJRSQ**		**N**	**RSQ**	**ADJRSQ**	
	15,106	0.0512	0.0506		15,106	0.0519	0.0512	

Industry fixed effects are included, and standard errors are clustered by firm and year.

Variables - which can also be found in Appendix A - are defined as follows:
EU: Earnings uncertainty, calculated per Donelson and Resutek (2015), as described in the text. *LCOMP:* the disaggregate earnings based measure of comparability. *TCOMP*: An accrual based measure of comparability, as defined in the text. *SUE:* Absolute value of unexpected earnings, scaled by the stock price at the end of the prior year, where unexpected earnings is actual earnings less a forecast based on a seasonal-adjusted random walk time-series model. *NEG_UE*: Indicator variable that equals one if firm-I has earnings are below the reported earnings a year ago, zero otherwise. *LOSS:* Indicator variable that equals one if the current earnings are less than zero, zero otherwise. *NEG_SI:* Absolute value of the special item deflated by total assets if negative, zero otherwise. *DAYS:* Logarithm of the number of days from the forecast date to the earnings announcement date. *SIZE: L*ogarithm of the market value of equity measured at the end of the year. *EPRED: R*-squared of a regression of annual earnings on prior-year annual earnings for the same firm. *EVOL:* Standard deviation of 16 quarterly earnings. *RVOL:* Standard deviation of 48 months of stock returns.